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CLIMATE CHANGE-DRIVEN COASTAL EROSION MODELLING IN TEMPERATE SANDY BEACHES: METHODS AND UNCERTAINTY TREATMENT

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Abstract

Developing future projections of shoreline change requires a good understanding of the driving coastal processes. These processes result primarily from the combination of mean sea level, waves, storm surges and tides, which are affected by global and regional climate change, and whose uncertainty increases with time. This paper reviews the current state of the art of methods used to model climate change-induced coastal erosion focusing on how climate change-related drivers and the associated uncertainty are considered. We identify research gaps, describe and analyse the key components of a comprehensive framework to derive future estimates of shoreline change and make suggestions for good practice. Within the scope of the review, we find that although significant progress has been made over the last decade, most of the studies limit uncertainty sampling to considering ranges of variation of forcing variables and ensembles of emissions scenarios, and applications with high level of probabilistic development remain few. Further research is necessary to fully (a) incorporate projected time series of coastal drivers into the erosion models, including bias correction; (b) sufficiently sample the uncertainty associated with each step of the top-down approach, including the consideration of different emission scenarios, inter- and intra-model variability, and multiple runs of erosion models or model ensembles; and (c) reduce uncertainty in shoreline change estimates by developing better datasets and model parameterisations, and progressing in detection and attribution.

Keywords: climate change; sandy beaches; coastal erosion modelling; uncertainty treatment.

1. Introduction

Managing coastal erosion under climate change is increasingly recognising the need for reliable projections of shoreline change across time scales up to multidecadal and centennial. This information has many uses including defining setback lines and planning for the relocation of coastal assets (Wainwright et al., 2015; Jongejan et al., 2016), anticipating potential losses of flood protection (Stripling et al., 2017) and recreation (Toimil et al., 2018; Mehvar et al., 2018), and deciding whether to implement protection measures (e.g., beach nourishment). However, modelling coastal erosion at these timescales raises significant challenges. One challenge is that the long-term evolution of the shoreline involves interacting and coupled short- to long-term coastal processes. Although this has been recognised in the literature (Toimil et al., 2020), there is no consensus on how to model such long-term complex interplays appropriately beyond just a few years (Ranasinghe, 2016; Robinet et al., 2018). Another challenge is that short- and long-term drivers shaping the coast are altered by climate change, leading to additional uncertainty to current conditions and potential significant impacts on future shoreline evolution. However, while assuming an increase in mean sea level and no changes in storminess is a common approach (e.g., Ranasinghe et al., 2012; Wainwright et al., 2015; Jongejan et al., 2016; Le Cozannet et al., 2019), little effort has been made to fully incorporate projections of waves (e.g., Zacharioudaki and Reeve, 2010; Casas-Prat et al., 2016), storm surges or river discharge, and even less to consider their combination. Finally, future estimates of shoreline change are influenced by uncertainties that arise from multiple sources (e.g., emissions scenarios, climate models, downscaling techniques, erosion models, data), which cascade through the complete modelling process, and accumulate in the final outcome (Ranasinghe, 2016). Since different coastal adaptation practitioners may have different preferences and acceptable degrees of risk (Losada et al., 2019), the need to communicate this uncertainty to end users and incorporate it into decision analysis has been recognised (Hinkel et al., 2019). For example, coastal managers could be provided with knowledge on the mean or median shoreline position, its variance (e.g., the maximum beach retreat in 5, 10, 25 and 50 years), and the associated uncertainty, for any geomorphic setting, scenario and time frame.

The release of the Intergovernmental Panel on Climate Change (IPCC) 4th Assessment Report (AR4) in 2007 was a turning point in several aspects. These included more evidence of the link between multiple physical impacts and climate change; observations of increasing temperatures, widespread loss of snow and ice, and rising global mean sea level; and increased confidence that extreme weather events will become more frequent in some regions and alter impacts such as coastal erosion. Importantly, it was recognised that although most attention was focused on sea-level rise and the associated inundation risk, erosion is another concerning coastal impact, and it requires projections of other coastal drivers including waves and surges (Hemer et al., 2010). Thus, methods that use projections of climate change-related drivers other than SLR and apply physics-based models able to simulate shoreline changes due to different forcings and consider uncertainty in some way (with a certain level of probabilistic development) are post AR4. Prior to AR4, coastal erosion approaches to estimate climate change-induced erosion were fundamentally based on a deterministic application of the Bruun Rule.

The study of the future evolution of the world's coasts requires a comprehensive framework that considers all climate drivers shaping the shorelines, including climate change and a quantification of the associated uncertainty. This paper aims to review the current state of the art of methods used to model climate change-induced coastal erosion, placing a special emphasis on how projected drivers feed erosion models and how uncertainties are treated therein. Furthermore, we analyse the key components that such a comprehensive framework would include, particularly those that have not been sufficiently considered to date. Our review includes the works published since the AR4 release in which methods to derive future shoreline changes are developed for and/or applied to mainland sandy beaches (both uninterrupted and inlet-interrupted) in temperate environments. Our current knowledge about future atmospheric processes in tropical and polar areas is still very limited and future projections of climate change-related drivers in these regions (e.g., tropical cyclones and coral-related processes in the tropics, and ice-related processes in the poles) could be even more uncertain than for the rest of the world (Morim et al., 2019). Methods that use projections of climate change-related coastal erosion drivers (SLR, storm surges and waves) usually apply physics-based models. These models allow to efficiently simulate shoreline changes due to different drivers and consider uncertainty. Index-based and multicriteria analysis that do not specifically provide physics-based erosion estimates but vulnerability ranking (e.g., Gornitz, 1991; Alexandrakis and Poulos, 2014; Pantusa et al., 2018) are therefore excluded. Finally, inlet-related effects are considered in terms of the impacts of these systems on adjacent beaches (mainland), neglecting other morphodynamic interactions.

The paper is structured as follows. Section 2 examines the main coastal drivers and processes responsible for shoreline change. Section 3 analyses the effects of climate change on coastal erosion drivers and their potential consequences on shoreline evolution. Section 4 describes the cascade of uncertainty and dealing-with options. Section 5 reviews existing methods to model climate change-driven coastal erosion. Section 6 identifies research gaps to be addressed and discusses the key components of a comprehensive framework to model future shoreline changes in which uncertainty is sufficiently sampled. Finally, Section 7 presents concluding remarks and provides several suggestions for good practice.

2. Coastal drivers and processes responsible for shoreline change

Coastal drivers and processes shaping shorelines occur across different time scales (Stive et al., 2002; Cowell et al., 2003). Short-term drivers such as waves, storm surges, tides, and extreme fluvial discharges play fundamental roles in forcing short- (storm to interannual scale) and mid-term (multiannual to decadal scale) shoreline change (e.g., Yates et al., 2009; Splinter et al., 2014; Barnard et al., 2015). For example, unusually large shoreline recession can result from extreme conditions such as winter storms that persist over hours and days. These shoreline retreats can accumulate and grow if clusters of storms impact upon the coast (Coco et al., 2014), hampering beach recovery (Lee et al., 1998; Birkemeier et al., 1999; Dodet et al., 2019). Ultimately, the continuous erosion or accretion over months and years governs the seasonal and multiannual shoreline evolution patterns (e.g., Miller and Dean, 2004; Maspataud et al., 2009). Longer-term drivers and processes including slow-onset relative sea-level change, aeolian transport, natural soil erodibility, chronic fluvial sediment supply/lack of supply, and alongshore gradients in longshore transport are mainly responsible for long-term (and possibly chronic) shoreline changes (multidecadal to centennial scale) (Ashton and Murray, 2006; Sallenger et al., 2012).

The relative contribution of the different coastal processes to the sediment budget, and hence to shoreline change is case-specific and strongly linked to the geomorphic setting. Here, we adopted the general division made by Ranasinghe (2016), distinguishing between the coasts that are interrupted by inlets and those that do not (inlet-interrupted and uninterrupted thereinafter). In uninterrupted coasts we consider small pocket, long embayed and open beaches. Small pocket beaches experience limited or no net longshore sediment transport change, as diffraction and refraction effects compensate within the enclosed boundaries. In some cases, however, pocket beaches can have certain alongshore variability and rotate in response to wave action (Turki et al., 2013). Long embayed beaches also have limited net longshore sediment transport change although typically experience considerable alongshore variability (Burvingt et al., 2017). These beaches are generally aligned with the prevailing wave direction and are highly sensitive to small changes on this direction. Modelling shoreline change appropriately on long embayed beaches would therefore require the consideration of any shifts in wave direction and subsequent beach rotation. For instance, embayed beaches can oscillate and rotate cyclically due to event-based and seasonal variations in mean wave direction in the short term (Short and Masselink, 1999; Masselink and Patriarchic, 2001), and slightly change their mean orientation over longer timescales (Harley, et al., 2011; Zacharioudaki and Reeve, 2011). The shoreline interannual variability in embayed beaches can be largely attributed to large-scale climate fluctuations described by teleconnection pattern indices such as the North Atlantic Oscillation (NAO) in the NE Atlantic coast (Thomas et al., 2011; Silva et al. 2012), the Arctic Oscillation (AO) and the Southern Oscillation Index (SOI) in the NW Pacific coast (Ranasinghe et al., 2004; Kuriyama et al., 2012), and El Niño-Southern Oscillation (ENSO), the Subtropical Ridge (STR) and the Southern Annular Mode (SAM) in the SE Australian coast (Barnard et al., 2015; Kelly et al., 2019). Open beaches can experience large net longshore and cross-shore sediment transport changes (Vitousek et al., 2017; Robinet et al., 2018). In these beaches, regardless twenty-first century SLR, alongshore gradients in longshore sediment transport have long been assumed as the main shoreline change driver on long timescales (Cowell et al., 2003). On shorter timescales, cross-shore processes play a major role, controlling shoreline variability and extreme retreats. Finally, beaches near inlets have a more complex behaviour, as they are influenced by the climate change-driven drivers affecting uninterrupted coasts plus the effects of adjacent inlets (Ranasinghe et al., 2013; Toimil et al., 2017; Bamunawala et al., 2019). Inlets such as estuaries or barrier-islands inlets can alter the longshore transport along a shoreline by acting as sinks or sources.

Short- and long-term climate-related coastal processes shaping shorelines are further modified by human action (Dean and Dalrymple, 2001). Examples include the rapid (and uncontrolled) development of coastal areas such (e.g., building on dunes) (Anthony et al. 2014); ports, navigational channels and jetties affecting sediment movement patterns (Saengsupavanich et al., 2008); groin fields causing sediment starvation or accumulation (Galgano, 2004); seawalls accelerating beach erosion by reflecting wave energy off the facing wall and reducing sediment input (Griggs, 1994); dams on rivers reducing sand supply to the coast (Frihy et al., 1991); sand mining of beaches and river beds that supply sand to these beaches (Anthony et al., 2015); and water level-related issues such as hydrocarbon and groundwater extraction, which can induce local ground subsidence and associated coastal inundation and erosion (Erban et al., 2014).

During the last decade, increasing emphasis has been placed on detection and attribution of coastal impacts (e.g., beach erosion) to their forcing (Cramer et al., 2014). Impact detection consists of identifying changes beyond a specified baseline, while attribution addresses the magnitude of these changes in relation to the influences of natural variability and human-related activities. Since some impacts are expected to have occurred in the past, both detection and attribution offer a form of validating and refining our projections about future changes, allowing the reduction of uncertainty in the modelling phase (Karl and Trenberth, 2003). This sort of extrapolation faces many limitations due to the complex and non-linear behaviour of beaches and because the absence of past impacts cannot constitute evidence against the possibility of future impacts. Furthermore, validating a model for current climate does not guarantee that it would perform well in the future, for example, if sea-level rise (SLR) exceeds the rates observed today. Nevertheless, it is not contested that the detection and attribution of shoreline changes are valuable to risk assessments (Stone et al., 2013). However, even when it is possible to detect an impact (e.g., observed shoreline retreat), more detailed understanding is required for attribution. It is currently generally understood that the impacts of human interventions have a major influence on coastal changes, but this does not mean that the effects of climate change and variability are negligible (Mentaschi et al., 2018). A formal attribution involving precise quantification is particularly challenging for coastal erosion due to the lack of high-resolution, continuous and long-term observations (more than 50-year records) of shoreline changes, and because disentangling the erosion led by climate-related coastal processes involves precise knowledge of the effects of other drivers. The latter point has a double constraint – the combined effect of climate and human drivers are non-linear and non-local in both space and time, implying lagged shoreline responses and transregional effects that can be tough to be understood, disentangled and quantified; and the ability of many beaches to self-adapt to climate changes further complicates the situation (Nicholls et al., 2016; Stone et al., 2013; Cramer et al., 2014). In what follows, we set aside human-induced perturbations and focus on how global and regional climate change can alter climate-related drivers, and thus future coastal processes and resulting shoreline change.

3. Climate change effects on coastal drivers and consequences on shoreline evolution

Climate change is altering mean sea level, mean and extreme wave conditions, storm surges, extreme sea levels, and river discharge (Wong et al., 2014). Changes in these climate-related drivers and the potential associated impacts on shoreline change are discussed below.

3.1. Changes in mean sea level

Based on process-based model studies, the IPCC in its 5th Assessment Report (AR5) estimated that global mean sea level was likely to rise 28-98 cm by 2100 above the 1986-2005 average, depending on the radiative forcing scenario (Church et al., 2013a), although not excluding a larger rise (Church et al., 2013b). Specifically, the AR5 gave a probability of up to 16.5% to exceed the upper bound of this range by 2100 and estimated that only a collapse of the marine ice-sheets in Antarctica could lead to SLR exceeding 1 m by the end of the century. However, two processes were not included in AR5: (1) marine ice-sheets instability, which is potentially underway for two major glaciers of Western Antarctica (Favier et al., 2014; Joughin et al., 2014) and may lead to contributions to SLR of up to 30 cm by 2100 (Golledge et al., 2015); and (2) marine ice-cliff instability, which could lead to contributions of Antarctica alone in the order of 1 m by 2100 (DeConto and Pollard, 2016), but which can happen only with large amounts of meltwater in Antarctica. While it is unsure that the latter process can occur during the 21st century (Edwards et al., 2019), it cannot be excluded considering feedback mechanisms such as the meltwater induced ocean warming recently indicated by Bronselaer et al. (2019). The IPCC report on the Ocean and Cryosphere (SROCC) raised the likely range of global SLR projections by 10 cm to incorporate the marine ice-sheets instabilities, although it does not preclude higher changes (Oppenheimer et al., 2019). Hence, due to our incomplete knowledge of the contribution of the Antarctic ice-sheet, when modelling coastal impacts such as coastal erosion it might be prudent to consider SLR scenarios beyond the AR5 and SROCC likely ranges (e.g., Nicholls et al., 2014; Hinkel et al., 2019).

When assessing SLR impacts, it is important to consider local SLR rather than the global mean. Local or relative SLR comprises global and regional ocean changes, and local uplift or subsidence components induced by processes of both natural and anthropogenic origin (Nicholls and Cazenave, 2010). Regional sea-level changes display differences with global estimates due to changes in ocean density and circulation, changes in atmospheric pressure and changes in Earth Gravity, Earth Rotation and viscoelastic solid-Earth deformation in response to mass redistributions such as ice melting and groundwater extractions (Mitrovica et al. 2009; Slangen et al., 2012; Gregory et al., 2019). Relative SLR may cause the chronic retreat of many coasts worldwide, either directly through the landward and upward displacement of the coastline (Bruun, 1962), or indirectly, by inducing sand volumes being trapped in inlet systems (Stive and Wand, 2003; van Goor et al., 2003).

Where the nearshore bathymetry remains unaltered, changes in mean sea level could also have relevant effects on nearshore hydrodynamics, resulting in more instances of extreme level thresholds being reached at the shorefront (Vitousek et al., 2017; Wahl et al., 2017; Vousdoukas et al., 2018), and the possible amplification of storm surges, tides, waves and river discharge due to changing non-linear interactions (Arns et al., 2017; Idier et al., 2017). The latter can make a significant contribution to the total water level at the coast, for instance, raising design heights by an average of 48-56% relative to design changes caused by SLR alone (Arns et al., 2017). Although these interactions have not yet been explored in coastal erosion, it is important to note that even moderate increases in mean sea level could lead to a significant increase in the number of episodic climate-related extreme retreat events (Toimil et al., 2017).

3.2. Changes in mean and extreme wave conditions

Climate change is expected to alter mean and extreme wave conditions (Wong et al., 2014; Morim et al., 2019). Variations in mean waves could result in increases or decreases in longshore drift (Idier et al., 2013) and changes in the magnitude and frequency of oscillation and/or rotation cycles in long-embayed beaches (Ranasinghe, 2016); the second could cause more instances of erosion thresholds being exceeded. Historical observations of global wave power were investigated by Reguero et al. (2019), who found changes of around 0.4% per year since 1948 due to upper ocean warming. The analysis of global satellite data also confirmed small increases in mean wind speed and wave height in the Southern Ocean over this period, with stronger increases in extreme conditions (90th percentiles) in the past 30 years (Young and Ribal, 2019). Concerning future projections, Hemer et al.'s (2013) dynamical approach showed an increase of around 10% in Southern Ocean mean significant wave heights (H_{sm}) and a decrease in North Atlantic wave generation, with changes in H_{sm} of similar magnitude. Increases and decreases of approximately 0.5s in the annual mean wave period were found in these regions, respectively. The projected response in wave direction showed a general trend towards a greater southerly component to mean wave direction (~3–5° directional shift) throughout the global ocean. A similar pattern was observed in Camus et al.'s (2017) statistical projections, which suggested annual H_{sm} increases in the Southern Ocean and eastern Pacific, and decreases in the North Atlantic Ocean, western North Pacific basin, Indian Ocean and Southern Hemisphere midlatitudes, with the magnitude of the increases four times higher than the magnitude of the decreases. Regarding the annual peak period changes, the authors found increases in the Southern Ocean, Eastern Pacific and Indian Ocean, and decreases in the North Atlantic Ocean and the Western Pacific Ocean until the Tropic of Capricorn.

Wang et al.'s (2014) statistical projections consistently indicated that the occurrence frequency of the present-day 1-in-10-year extreme wave heights is likely to double or triple in many coastal regions around the world, although not everywhere (e.g. the Atlantic European coast exhibit a decrease), considering a high radiative forcing scenario by the end of the century. For the same scenario and time horizon, Mentashi et al. (2017) conducted a global analysis of changes in extreme energy fluxes, showing a significant increase up to 30% in the 1-in-100-year return level for the majority of the coastal areas of the southern temperate zone, and a negative trend in the Northern Hemisphere. Later, Briceno and Wolf's (2018) work highlighted a projected decrease in H_{sm} of the order 0.2 m across most of the European coast and an increase in annual maximum and the 99th percentile of H_s of about 0.5 – 1 m in some areas, suggesting an increased intensity of rare high wave events in the future. Casas-Prat et al.'s (2018) dynamic projections including the entire Arctic Ocean agreed on a projected increase in surface wind speed in the Southern Hemisphere mid-high latitudes and additionally indicated that higher waves would be accompanied with increased peak wave period and increased wave age in the East Pacific and Indian Oceans, and a significant counter clockwise rotation in the mean wave direction in the Southern Oceans. More recently, Lemos et al. (2019) presented projected global mean wind speed, wave height, wave period and wave energy flux towards the mid-twenty first century, which indicate increases in the mid-to-high latitudes of the Southern Hemisphere and in equatorial areas and decreases in the tropical and subtropical latitudes of the Northern Hemisphere.

Despite the large inconsistencies between methodologies, there is strong consensus in the projected signal of change in both the mean and extreme ocean wind-wave height over the end of this century across 15 and 5 out of 21 ocean regions, respectively. This has resulted from the consensus-based analysis conducted by Morim et al. (2018) to establish consistent patterns of impacts of global warming on the wind-wave climate across the globe. More recently, Morim et al. (2019) illustrated a summary of robust projected changes in offshore multivariate wave conditions in the vicinity of the world's coastlines. These studies evidenced that current research is more focused on changes in wave height than in wave period and direction, although the latter may have important implications. For example, longer wave periods could lead to larger erosion volumes and landward retreat (e.g., van Gent et al., 2008; Castelle et al., 2015), and variations in wave direction may significantly affect longshore sediment transport patterns (e.g., Adams et al., 2011; Harley et al., 2017). Additionally, in oscillatory embayed systems around many parts of the world, major changes in coastal responses are associated with changes in wave period and direction. For instance, the Interdecadal Pacific Oscillation changes the wave attack direction on Australian East Coast beaches through interactions with ENSO, STR, and SAM (Goodwin 2005; Kelly et al., 2019). Since these phenomena are expected to change their latitude and intensity under different radiative forcing scenarios (Wang and Cai, 2013; Yang et al., 2018), wave height and direction, and hence sediment transport may be affected.

3.3. Changes in storm surges and extreme sea levels

Storm surges are also significant features of the extreme coastal climate, which can contribute to higher total water levels at the shorefront and exacerbate episodic coastal erosion (Kriebel and Dean, 1985; Zhang et al., 2002). Published studies on storm surge changes have been limited to the analysis of extreme sea levels (ESL) resulting from the combination of mean sea level, tidal oscillations and storm surges, from long-term observations at a limited set of stations worldwide. These changes were found to be mainly driven by mean sea level variations (Menéndez and Woodworth, 2010). Removing this contribution, decadal and multidecadal variations of extremes events unrelated with mean sea level were detected and attributed to large-scale patterns of climate variability (e.g., the North Atlantic Oscillation), which cannot be described by linear trends (Wahl and Chambers, 2015; Marcos et al., 2015). Considering different radiative forcing scenarios and return periods, Vousdoukas et al. (2016) projected a slight increase in storm surge levels along the European coast, with regions below 50°N showing minimal change or a small decrease, except for the highest radiative forcing by 2100, for which a moderate increase was indicated. Lee et al. (2017), consistent with previous studies (e.g., Bender et al., 2010; Grinsted et al., 2013), identified a positive correlation between global mean temperature rise and increasing frequencies of Atlantic extreme storm surges. The strength of this relationship however was found uncertain and only confidently detectable within a multidecadal timescale.

Future changes in all the components of ESLs along Europe's coasts (considering mean sea level, tides, waves and storm surges) were analysed by Vousdoukas et al. (2017). The authors found that by the end of this century, the 1-in-100-year ESL is on average projected to increase by 81 cm for the highest radiative forcing scenario, and that changes in storm surges and waves enhance the effects of relative SLR along the majority of northern European coasts, locally with contributions up to 40%. More recently, Vousdoukas et al. (2018) presented global dynamic probabilistic projections of ESLs, which indicated a very likely increase of the global average 1-in-100-year ESL of 58–172 cm under the highest radiative forcing scenario, mostly due to mean sea-level rise. That rise in ESLs could result in an unprecedented frequency of extreme coastal erosion events along many parts of the world.

3.4. Changes in river discharge

Finally, climate change could produce large variations in river flows and the associated solid discharge due to increased evapotranspiration, changing precipitation and snow (Wong et al., 2014; Gattuso et al., 2015). For instance, Nakaegawa et al. (2013) projected future discharges of major global rivers in the late twenty-first century. These projections suggested increases in annual mean river discharges in high latitudes, in India and the south-eastern United States but decreases in broad regions of Europe, western Asia, the western United States, Central America, and the southern half of the Amazon River basin. Shortly after, Santini and di Paola (2015) projected an overall global decrease in mean annual discharge over both the medium and long term considering different radiative forcing scenarios. This trend is especially relevant for coasts near inlets, where increases or decreases in fluvial discharge may cause decreases or increases of shoreline retreat, respectively (Ranasinghe et al., 2013).

4. Addressing uncertainty

Future projections of long-term and storm erosion are predominantly assessed to date using top-down or scenario-led approaches (Zscheischler et al., 2018). This perspective involves undertaking a sequence of steps in which information cascades from one step to the next, and so does the associated uncertainty (Wilby and Dessai, 2010). Such expansion of the envelope of uncertainty through the model chain has been widely described in the literature using the paradigm of the cascade of uncertainty (Mitchell and Hulme, 1999).

4.1. The cascade of uncertainty in climate change-driven erosion modelling

Here we adopt the broad structure that a thorough climate change impact quantification study would ideally follow suggested by Ranasinghe (2016). The first step consists of the generation of scenarios of atmospheric greenhouse gas (GHG) emissions based on hypothetical socio-economic and demographic pathways. Biogeochemical models are then applied to translate emissions scenarios into GHG and aerosol concentration scenarios, which are the fundamental input to coupled atmosphere-ocean Global Climate Models (GCMs) for producing climate projections at the global scale. In a subsequent step, global climate projections can be downscaled to the regional/local scale using dynamic (through Regional Climate Models, RCMs) or statistical downscaling methods (Laugel et al., 2014). GCMs and RCMs do not include information on coastal drivers. Instead, they provide climate variables (e.g., wind, sea-level pressure and ice coverage) that are used to predict future changes in waves and storm surges statistics (e.g., Camus et al., 2017), or as forcings for wave generation or ocean circulation numerical models to dynamically generate time series of these dynamics (e.g., Casas-Prat et al., 2018). The downscaling output therefore conditions the erosion modelling approach (i.e., future statistics vs time series). Generating future time series from statistical downscaling output could be possible but it would require additional steps (Toimil et al., 2017). The selection of GCMs and RCMs (with horizontal grid spacing of typically 0.56º-3.75º and 0.11º-0.44º, respectively) can be influenced by many factors, inter alia, whether the variables of interest proceed from the same model realisation, initialisation and physics, if they are available for the scenarios and time periods needed, and if they would allow obtaining time series of drivers at the required resolution (e.g., it would be unrealistic to use monthly wind fields to derive hourly time series of waves). Importantly, the resulting time series of drivers requires bias correction. The following step within the top-down approach may involve the application of regional coastal forcing models if more detailed spatial scales are required (e.g., transference of coastal drivers to the beach). Finally, projected coastal drivers are fed into erosion models (e.g., to estimate the possible evolution of the shoreline over the simulated period). These models ideally need to be simulated with hundreds of combinations of forcing variables to sufficiently quantify the uncertainty that accumulates through the multiple model tiers in the top-down approach (e.g., using the Monte Carlo method). This comprehensive sequence of steps is displayed in **Fig. 1**.

The paradigm of the cascade of uncertainty has traditionally assumed that biases from GCMs and RCMs are independent and behave approximately additive, and thus that uncertainty increases when global data is translated into regional data (Sørland et al., 2018). This would indicate that using GCMs to drive RCMs would not lead to intrinsic improvements or more reliable results beyond higher-resolution details or 'more detailed noise' (Keer, 2013). It is evident that RCMs cannot modify the larger-scale atmospheric circulation and thus it is not obvious if they can improve larger scale properties (Rammukainen, 2010). It has been proven however that RCMs can in some cases reduce the biases compared to the driving GCM in the control period (Sørland et al., 2018), although there is no guarantee of the same influence on the climate change signal (Teichmann et al., 2013). While any definitive conclusion can be drawn in one direction or the other, evidence suggests that the propagation of uncertainty from top to bottom could not be a monotonically increasing phenomenon in all situations. In either case, even if uncertainty reduces at the GCM-RCM step, the number of permutations grows through the model chain as the possibility of GCM-RCM combinations also increases.

Two types of uncertainty can be identified throughout this process: (1) Knowledge Uncertainty (KU) due to our imperfect knowledge of the climate change problem; and (2) Intrinsic Uncertainty (IU), which is inherent to the problem (Giorgi, 2010). For example, the uncertainty associated with emissions scenarios and internal variability of the climate system can be considered as IU (see **Fig 1**). The IPCC in AR5 uses four Representative Concentration Pathways (RCP2.6, RCP4.5, RCP6.0 and RCP8.5, Moss et al., 2010) corresponding to different trajectories of GHG emissions. RCPs include implicit policy actions to achieve mitigation and were selected to illustrate different targets in terms of radiative forcing at 2100. The IU associated with climate variability is overall addressed through ensembles of transient and credible simulations starting at different times in the control period. KU (categorized as "bad" uncertainty) is mainly due, but not limited to the following aspects (also shown in **Fig 1**): 1) an approximate representation of the relevant processes in biogeochemical models (concentration scenario uncertainty); 2) many different descriptions of dynamic and physical processes (GCM-RCM configuration uncertainty); 3) systematic model errors (bias uncertainty); 4) the application of downscaling methods to provide climate information at the resolution required by coastal erosion models (downscaling uncertainty); and 5) the development and implementation of coastal erosion models, provided our incomplete understanding of coastal processes and sediment-transport mechanisms, as well as limited computational resources (epistemic and aleatory uncertainty, respectively). KU needs to be reduced as much as possible to advance science understanding, with the paradox that an increase in knowledge may lead to discovering new processes ultimately increasing uncertainty (Giorgi, 2010).

These two types of uncertainty can be quantified in different ways or described qualitatively (Mastrandrea et al., 2010). However, quantitative descriptors of uncertainties provided by the climate science community generally do not cover the full range of possible outcomes, often excluding low-probability high-impact outcomes, which can be relevant for decision making on coastal adaptation (Hinkel et al., 2019).

The importance of uncertainty depends on many different factors (Giorgi, 2010), including the time horizon of the projection, the climate-related variable considered and the scale at which the erosion model is applied. Overall, scenario and GCM-RCM configuration uncertainty dominate long-term climate change, especially at the global scale. The internal variability becomes of primary importance for short- and mid-term twenty-first century projections and higher order climate statistics. For example, the uncertainty associated with downscaling approaches dominates over scenario and GCM-RCM configuration uncertainty in global wave climate projections (Hemer et al., 2013; Morim et al., 2018; Morim et al., 2019). Uncertainty in the erosion models can account for the 20-40% of uncertainty in shoreline change projections by 2100 (Le Cozannet et a., 2019).

When assessing climate change-driven coastal erosion, two simplifications usually apply. The first relates to the difficulty of implementing top-down approaches to assess impacts produced by multiple interacting drivers. Long-term shoreline changes result from the combined effect of multiple drivers and hazards in the weather and climate domain spanning over a range of temporal scales (i.e., compound weather and climate events, Zscheischler et al., 2018). For this reason, to date the effect of climate change has been considered primarily in a single driver (e.g., SLR in Ranasinghe et al., 2012; wave projections in Casas-Prat el al., 2016) or, if in more than one driver, in each of them independently (e.g., SLR and wave projections in Vitousek et al., 2017; SLR and changes in river discharge in Ranasinghe et al., 2013).

The second simplification is associated with the challenge of conducting a full uncertainty quantification. Probabilistic frameworks offer great promise in assessing uncertainty from different sources. However, an impracticable number of simulations would be required to sample the full uncertainty space covering multiple emissions scenarios, different GCM-RCM configurations, internal variability, bias correction, downscaling methods, and erosion model parametrization and implementation. To date, most assessments of climate change-driven coastal erosion have limited the exploration of the uncertainty space mainly to individual dimensions. This is the case of addressing uncertainty in GCM-RCM configuration using a reduced number of GCMs or RCMs for a particular scenario (e.g., Casas-Prat el al., 2016); and modelling the shoreline evolution probabilistically using thousands of synthetic multi-variate time-series of waves and storm surges, but considering only a few potential SLR trajectories (e.g., Toimil et al., 2017). Multiple runs of the erosion model would ideally be needed to draw random samples from appropriate distributions fitted to the range of values of the forcing variables, which already considers the uncertainty accumulated through the top-down approach (Ranasinghe, 2016).

4.2. Approaches to address uncertainty in climate change-driven coastal erosion modelling

Current approaches to address uncertainty in the assessment of climate change-driven coastal erosion are displayed in **Table 1**. They include deterministic, multiple-deterministic, ensemble, objective/subjective-probability and probabilistic approaches, which start from no uncertainty consideration and then are ranked in order of increasing uncertainty sampling, although with some nuances. Deterministic approaches involve a single model simulation with a single set of forcing variables, providing single-value estimates of coastal erosion with high uncertainty that is not quantified. Multiple-deterministic approaches sample uncertainty to some degree by considering ranges of values of forcing variables (typically the mean or median value and the variance corresponding to a single GHG emissions scenario or an RCP for a given time horizon) or input parameters, yielding a range of associated coastal erosion estimates. Assessments that use ensembles go one step further by considering uncertainty that cascades through the top-down approach. This can be achieved, inter alia, by incorporating forcing variables related to a set of scenarios (e.g., GHG emissions scenarios or RCPs) and/or a set of GCM-RCM configurations, or by applying more than one erosion model. Results can be expressed on an individual basis for each scenario, GCM-RCM configuration, and erosion model, or as a statistical aggregate of the ensembles considered. The forcing variables associated with the scenarios considered in the ensemble approach can be couched in deterministic or multiple-deterministic terms (single value or range of values, respectively). Objective/subjective-probability methods characterise coastal erosion drivers and processes, and model parameters using probability distributions. Objective and subjective probability distributions are derived from observations and expert judgement, respectively. This approach does not fully implement statistical models in order to generate "real" synthetic conditions for erosion models, and hence cannot sufficiently quantify the uncertainty that accumulates through the model tiers (**Fig. 1**). Finally, probabilistic approaches apply statistical models (e.g., joint probabilities, copulas, autoregressive models, etc.) and undertake multiple runs of the erosion model to simulate random samples from appropriate distributions fitted to the range of values of the forcing variables. These forcing variables derive from regional coastal forcing models and already incorporate the uncertainty introduced by the GHG and aerosol concentration scenarios and GCM-RCM configurations. Both objective/subjective-probability and probabilistic approaches can provide probabilistic estimates of shoreline change over time.

Uncertainty approaches	Descriptions adopted in this paper
Deterministic	Single set of input data, model configuration and model simulation, typically related to one GHG emissions scenario or RCP and for a given time horizon. Uncertainty is not considered. E.g., Rosati et al.'s (2013) model application using a single SLR value. E.g., Alexandrakis et al.'s (2015) model application using a representative value of significant wave height combined with a single SLR scenario (for three time slices).
Multiple-deterministic	Limited sets of input data, model configurations and model simulations, typically related to one GHG emissions scenario or RCP and for a given time horizon. Uncertainty is sampled by considering a range of variation of forcing variables or model parameters. E.g., Dean and Houston's (2016) model application using mean and standard deviation SLR values associated with the four RCPs.
Ensemble	Sets of input data, model configurations and model simulations, typically related to different GHG emissions scenarios or RCPs, GCM-RCM configurations, and erosion models, sampling the associated uncertainty that cascades through the top-down approach. Results can be expressed separately for each run, or in the form of statistic aggregates that are representative of the ensemble. E.g., Allenbach et al.'s (2015) approach using one model ensemble. E.g., Monioudi et al. 's (2017) approach using three model ensembles.
Objective/Subjective-probability	Input data and model parameters characterised through probability distributions. These approaches do not fully implement statistical models, instead they translate observations or expert opinions into objective or subjective probability distributions, respectively, which are can be used to propagate uncertainty across models. Results can be provided in terms of probabilistic estimates over time, typically related to different GHG emissions scenarios or RCPs. E.g., Le Cozannet et al.'s (2016) subjective-probability approach for idealized wave exposed sandy beaches in which the authors define probability functions for the parameters involved in the sand budget. E.g., Le Cozannet et al.'s (2019) objective-probability approach in which the authors define probability functions for the parameters involved in the sand budget. The values of the foreshore slopes are determined by considering the difference between two model approaches, one of them probabilistic.
Probabilistic	Input data and model parameters characterised through probability distributions. These approaches rely on the explicit application of statistical models and multiple realisations of the erosion model to provide random samples from appropriate distributions fitted to the range of values of the forcing variables derived from regional coastal forcing models, which already incorporate the uncertainty that cascades through the top-down approach. Results can be provided in terms of probabilistic estimates over time, typically related to different GHG emissions scenarios or RCPs. E.g., Ranasinghe et al.'s (2012) approach that combines probabilistic series of storm events and the mean value of SLR associated with one RCP. E.g., Toimil et al.'s (2017) approach that combines probabilistic multivariate series of waves and storm surges and the mean and standard deviation values of SLR associated with one RCP.

Table 1 Current approaches used to consider uncertainty in climate change-driven coastal erosion modelling.

Using the approaches described in **Table 1**, uncertainty can be considered in the coastal drivers modelling phase (box 1 in **Fig. 2**, from the GHG emissions scenarios to the generation of projected forcing variables to feed into the erosion models), in the coastal processes modelling phase (box 3 in **Fig. 2** e.g., through multiple realisations of the erosion model, or using an ensemble of models or model parameters), or in both (box 5 in **Fig. 2**, dark grey components). In either case, the uncertainty sampled is transferred to the outcome (box 4 in **Fig. 2**).

SLR is a key climate-change driver shaping future shorelines worldwide in the long-term. However, it is in turn a deeply uncertain process in terms of magnitude and rate of change, especially by the latter part of this century and beyond. This has led to a growing body of literature focused on studying SLR components and the associated uncertainty.

4.3. Uncertainty in sea-level rise as a key climate-change coastal driver

SLR is expected to amplify the episodic erosion from storms and drive chronic erosion on sandy shorelines (Ranasinghe, 2016). AR5 and SROCC SLR projections are obtained by summing different contributions such as the thermal expansion of ocean water, the melting of glaciers, ice caps and ice-sheets and changes in land water storage (Church et al., 2013; Oppenheimer et al., 2019). To produce global and regional projections, the AR5 sampled the uncertainty associated with these contributions, considering that for each RCP, SLR will "likely" (i.e., more than 67% probability, Mastrandrea et al., 2010) be within the 5-95% range, from modelling results based on the CMIP5 climate projections. A medium confidence is given to the likely range of sea-level projections delivered in AR5 based on a qualitative assessment of the outcome by IPCC authors.

However, AR5 and SROCC project SLR likely ranges excluding higher magnitudes of ice loss in Antarctica and Greenland, which only apply if less likely outcomes are included. Potential high-end impacts on shoreline changes would be underestimated if only SLR projections characterizing just likely sea-level changes are considered (Nicholls et al., 2014). As a result, high-end scenarios (i.e., possible although unlikely scenarios) for end-century global SLR have been proposed by many authors based on semi-empirical models (Rahmstorf, 2007), probabilistic projections (Jevrejeva et al., 2014), expert knowledge mainly associated with future ice-sheet contributions (Bamber and Aspinall, 2013; Horton et al., 2014), or by running models with particularly unfavourable settings (DeConto and Pollard, 2016; Hansen et al., 2016). Recent studies highlight the large inherent uncertainties associated with the potential rapid disintegration of the Antarctic Ice Sheet (DeConto and Pollard, 2016). These results were incorporated into updated probabilistic SLR projections (Le Bars et al., 2017; Kopp et al., 2017). Such unfavourable scenarios were also integrated into other uncertainty frameworks based on extra-probabilistic theories that seek to account for the uncertainty in probabilistic measures (i.e., upper and lower probability bounds) (Ben Abdallah et al., 2014; Le Cozannet et al., 2017).

The spatial variability of local SLR, which is an important driver of coastal erosion, arises from regional steric and ocean-dynamics effects, as well as from non-climatic effects such as glacio-isostatic adjustment, tectonics and sediment compaction (Wöppelmann and Marcos, 2016). Probabilistic local SLR projections are generally obtained combining 1) a joint probability distribution of global mean thermal expansion and regional ocean dynamics derived from a CMIP5 ensemble; 2) glacier mass-balance changes; 3) anthropogenic changes in land-water storage; 4) ice sheet contributions (including consideration of extreme contributions such as expert elicitation in Bamber and Aspinall, 2013, or physical model results including ice-shelf hydrofracturing and ice-cliff collapse in DeConto and Pollard, 2016); and 5) regional non-climatic effects based upon a spatiotemporal statistical model of tide-gauge observations (Kopp et al., 2014; Kopp et al., 2017), or GPS data in combination with other geodetic approaches (Wöppelmann et al., 2013). Uncertainty associated with SLR contributions for each of the individual components is sampled using each time-dependent probability distributions of cumulative contributions.

4.4. Approaches to address uncertainty in sea-level rise

Table 2 summarizes and describes the perspectives identified in the literature to address uncertainty in SLR projections, which take the no consideration of uncertainty as a starting point and then are ranked in order of increasing uncertainty sampling, although with some nuances. Deterministic SLR estimates are highly uncertain and typically correspond to the mean or median value of a GHG emissions scenario or to an RCP for a given time horizon. Multiple-deterministic ranges of SLR values typically refer to the mean or median value and variance associated with a GHG emissions scenario or with an RCP for a given time horizon. Ensembles consist of a set of SLR estimates, either single values or ranges, related to a set of scenarios, typically of GHG emissions or RCPs and for a given time horizon. It is common to work with statistics that are representative of the ensemble (e.g., in terms of percentiles), albeit not necessarily. Probabilistic SLR distributions usually provide complete probability density functions of SLR over time, which are typically associated with GHG emissions scenarios or RCPs. However, the tails of these distributions are highly uncertain, especially for the contribution from ice sheets and non-climate effects where subsidence is large (Stammer et al., 2019). Finally, extra-probabilistic SLR distributions seek to explicitly consider the imprecise and/or incomplete information in probabilistic confidence intervals, for example, by combining model outcomes and expert knowledge. Importantly, the different approaches can also be combined. For example, according to our terminology, AR5 and SROCC provide multiple-deterministic SLR projections (likely ranges) for an ensemble of RCPs based on the propagation of uncertainties summing sea-level change components. Further, in both AR5 and SROCC, the probability of each SLR component is derived from an ensemble approach (see Le Bars 2018 for detailed explanations of this procedure).

Uncertainty approaches	**Descriptions adopted in this paper**
Deterministic	Single SLR value, typically the mean or median value corresponding to a GHG emissions scenario or to an RCP. E.g., the RCP8.5 SLR median value.
Multiple-deterministic	Range of SLR values, typically the mean or median value and variance corresponding to a GHG emissions scenario or to an RCP. E.g., the RCP8.5 SLR likely range (the 5 to 95% range of the projections of CMIP5 models).
Ensemble	SLR values (single values or ranges) associated with more than one scenario, typically with GHG emissions scenarios or RCPs. These values can be used independently or in the form of statistic aggregates. E.g., SLR values associated with different RCPs. E.g., SLR values associated with Nicholls et al.'s (2014) high-end scenarios.
Probabilistic	Probability density function of SLR values, typically associated with GHG emissions scenarios or RCPs. E.g., Kopp et al.'s (2014) probabilistic SLR projections. E.g., Kopp et al.'s (2017) probabilistic SLR projections considering the potential rapid disintegration of the West Antarctic Ice Sheet.
Extra-probabilistic	Credible probability function of SLR values conveying aleatory uncertainties as well as uncertainties on the shape of the distribution itself. E.g., Ben Abdallah et al.'s (2014) approach using belief functions. E.g., Le Cozannet et al.'s (2017) approach based on the possibility theory.

Table 2 Current approaches used to consider uncertainty in SLR.

Deterministic, multiple-deterministic, ensemble and probabilistic approaches used to consider uncertainty in SLR have been implemented in assessments of climate change-driven shoreline changes (see examples in **Table 1**). As it will be shown in the literature review provided in **Section 5**, to date some research works still limit uncertainty sampling exclusively to SLR, mainly incorporating an ensemble of GHG emissions scenarios or RCPs.

5. Methods to assess climate change-driven shoreline evolution

Significant progress has been made over the last decade to develop a range of methods for the assessment of climate change-driven coastal erosion based on our present state of knowledge and resources. Modelling strategies composed of different physics-based (or empirical) models simulating cross-shore or long-shore processes, and other sinks or sources that contribute to the sediment budget have proven able to reproduce observed shoreline changes over a broad range of time scales to a fair degree of accuracy while accounting for uncertainty. In what follows, we review existing methods developed and/or applied to model climate change-driven shoreline changes in uninterrupted and inlet-interrupted coasts; identify their components; and discern the approaches used to sample uncertainty (from **Table 1** and **Table 2**).

In order to provide a coherent and streamlined assessment of the state-of-the-art, we assume that the key components that may be involved in a comprehensive modelling of climate change-driven coastal erosion can be organised as presented in **Fig. 2**. Many of these components have already been discussed above. From bottom to top in **Fig. 2**, the first challenge when it comes to developing projections of coastal erosion – namely mid- and long-term shoreline changes or storm erosion (box 4) – is to identify and simulate the responsible coastal processes (box 3). These coastal processes may differ among coastal typologies (box 2) and are generated by different combinations of coastal drivers such as mean sea level, waves, storm surges, tides and river discharge, which may be affected, directly or indirectly, by global and regional climate change (box 1). Finally, uncertainty arising from different sources and introduced at every step (see **Fig. 1**) can be considered using diverse approaches with different levels of robustness (box 5; see also **Table 1**).

The division in uninterrupted and inlet-interrupted coastlines (first level), and pocket, long-embayed and open beaches (second level) responds to organisation purposes and intends to be an informative, illustrative and clear way for coastal experts to follow the contents of this review. As this review is focused on methods rather than models, the models used do not fall into a specific category, but their applications do. Whenever the reviewed studies fall into more than one class (e.g., regional assessments that apply to different beach typologies), the classification criterion has been to include them in the category (or categories) in which we consider they could be more relevant.

Importantly, coastal processes and shoreline changes are linked to the geomorphic setting (e.g., the fact that in pocket beaches alongshore gradients in longshore sediment transport are often neglected), but it does not mean that every reviewed study considers all erosion drivers and includes all coastal processes relevant for the typology of beach they are analysing. Quite the opposite, many simplifying assumptions are made, and much remains to be done in this field of research.

5.1. Uninterrupted coasts

5.1.1. Small pocket beaches

Pocket beaches are typically small beaches located between headlands. Most studies in the literature ideally assume that little or no exchange of sediment occurs with adjacent coasts, neglecting alongshore gradients in longshore sediment transport within the sand budget (Vitousek et al., 2017). Over the last fifty years, the method most widely used to obtain projections of coastal recession due to SLR has been the Bruun Rule (Bruun, 1962). The Bruun Rule predicts the landward and upward displacement of the cross-shore profile in response to a rise in mean sea level. However, determining if this approach performs within acceptable limits is difficult, as SLR is at present a minor contributor to shoreline change on many world coasts. This has led numerous authors to question its adequacy e.g., demonstrating its conservationism, recommending it be abandoned (Cooper and Pilkey, 2004), suggesting only to consider it as broadly indicative estimates (Ranasinghe and Stive, 2009), and offering other alternatives (Rosati et al, 2013; Dean and Houston, 2016; Atkinson et al., 2018; Beuzen et al. 2018). These alternatives incorporate additional physical processes, which are relevant for shoreline change over different time scales.

Future shorelines at small pocket beaches will be shaped not only chronically by long-term SLR, but also episodically due to the action of short-term waves and local water levels. Only two approaches in this category consider these effects in combination: the methodology proposed by Toimil et al. (2017) to manage coastal erosion probabilistically at the regional scale; and the ensemble approach presented by Monioudi et al. (2017).

Toimil et al. (2017) developed a methodology to predict shoreline changes due to waves, storm surges, astronomical tides, and SLR probabilistically. Since the statistical projections of waves and storm surges developed by the authors using 40 GCMs showed very small changes, the approach relies on historical data and a vector autoregressive (VAR) model (Solari and van Gelder, 2012) to generate thousands of synthetic 90-year multivariate hourly time series of these dynamics with different chronologies. The time series are combined with the astronomical tide reconstructed over this century and three regional SLR curves (multiple-deterministic SLR approach using the RCP8.5 mean values and standard deviations) into a shoreline evolution model. The model comprises two modules: cross-shore transport due to wave setup, storm surges and astronomical tides following an equilibrium model (Miller and Dean, 2004); and cross-short transport due to SLR following an equilibrium beach profile change model (based on Bruun, 1962). The data and model allow hourly probabilistic estimates of extreme retreats, short- and mid-term shoreline variability, and long-term changes, as well as to quantify the associated uncertainty. Feeding high-resolution time series of drivers into the shoreline evolution model has the advantage of implicitly considering storm occurrence and grouping and beach recovery without the need of introducing additional variables into the stochastic simulation. In this study, which was undertaken in 52 pocket beaches along the North Spanish coast, uncertainty related to the top-down approach is sampled using a range of likely SLR values over the whole century associated with the RCP8.5 and multiple chronologies of waves and storm surges.

Monioudi et al. (2017) presented an assessment of the SLR-induced erosion on Aegean archipelago beaches (Greece), providing statistic aggregates for model ensembles. The authors apply the following seven cross-shore erosion models in stationary mode: Bruun (Bruun, 1988), Edelman (Edelman, 1972), Dean (Dean, 1991), SBEACH (Larson and Krauss, 1989), Leont'yev (Leont'yev, 1996), XBeach (Roelvink et al., 2010), and Boussinesq (Karambas and Koutitas, 2002). Two model ensembles are created: a "long-term" ensemble consisting of the Bruun, Dean and Edelman analytical models; and a "short-term" ensemble including the numerical SBEACH, Leont'yev, XBeach and Boussinesq models. The former is used to assess SLR-driven recession; and the latter to obtain beach retreat due to episodic extreme sea levels (i.e., due to storm surges and waves). Finally, a third model ensemble results from the combination of the other two. The models are run using a range of plausible energetic wave conditions (offshore significant wave heights of 1-4 m and associated periods of 4-8 s), seven median (d_{50}) grain sizes, five linear profile slopes, and eleven SLR scenarios (ensemble SLR approach assuming increases from 0.05 to 2 m). About 5500 experiments are carried out considering all the possible combinations, and the means (best fits) of the lowest and highest projections yielded by the models with equal weighting within the ensembles are the final outcomes. The approach is based on the proposition that as models have differential sensitivity to environmental factors, ensemble applications may provide more reliable ranges than individual models and consider uncertainty in the erosion models used (the last step in the top-down approach).

5.1.2. Long embayed beaches

Embayed beaches have shorelines of typically spiral-shaped curvature, in which climate change-induced variations in longshore and cross-shore sediment transport may lead to significant changes in their rotation and mean orientation, possibly resulting in their permanent re-alignment (Harley et al., 2015; Ranasinghe, 2016). Zacharioudaki and Reeve (2011) explored what the evolution of the coast around Poole Bay (UK) could be under a range of variations in future wave characteristics. Although considerably relevant to shoreline change, variations in mean sea level, tidal range and the swell component of wave conditions have been excluded from this work, which according to the authors was intended to be a preliminary study directly applicable to beaches exposed to little or no swell. The one-line model described in Zacharioudaki and Reeve (2010) is used to provide monthly and seasonal statistics of shoreline change for the time-slice 2071-2100 with respect to 1961-1990. In order to obtain time series of monthly or seasonal shoreline positions, the model is performed for individual 30-year time series of projected waves that combine two GCMs and a RCM run at two spatial resolutions, and with the shoreline set back to its initial shape after each shoreline shape output is derived. The authors adopted an ensemble approach, sampling uncertainty associated with two emission scenarios (A1 and B2 from Nakicenovic et al., 2000) and nine climate experiments.

Studies in embayed beaches also include the Probabilistic Coastline Recession (PCR) model first developed by Ranasinghe et al., (2012) and further applied by Wainwright et al. (2015) and Jongejan et al. (2016) at Narrabeen Beach (Sydney, Australia). The PCR model provides probabilistic estimates of net long-term coastal dune recession as a proxy for cross-shore beach displacement landwards due to the combined effect of storm erosion and SLR projections (McInnes et al., 2007). To that end, and assuming no changes in storminess over this century, 110-year time series of storms are generated using joint probability distributions of design storm characteristics within a Monte Carlo method (Callaghan et al.,

2008) in which storm grouping is included as an additional parameter. For each storm, SLR is also occurring (deterministic SLR approach), and dune recession is estimated using the dune impact model proposed by Larson et al. (2004). Beach recovery between storms that is obtained empirically and incorporated in the model. The authors concluded that the bootstrapping technique employed in the model (i.e., computing recessions until exceedance probabilities greater than 0.01% convergence) allows minimizing the uncertainty associated with predicted probabilistic estimates. The uncertainty sampled is therefore limited to the multiple time series of sequences of design storms and the associated multiple model runs, disregarding any other aspect related to the top-down approach.

Simpler assessments of shoreline change in other long embayed beaches include the works developed by Snoussi et al (2009), Yoshida et al. (2013) and Alexandrakis et al. (2015), which only consider cross-shore transport. Following earlier analysis (e.g. Nicholls and Leatherman, 1995), the first is a straightforward application of the Bruun Rule to determine the upward and landward displacement of the Tangier coast (Morocco) for an ensemble of three SLR scenarios (global-mean estimates) for the time horizons 2050 and 2100. The second projected shoreline recession by 2100 in five Japanese beaches using a parameterised Bruun Rule, in which the berm height is formulated in terms of the breaking significant wave height and the mean significant wave period. The authors developed a multiple-deterministic approach by extrapolating mean and maximum past trends of wave height variation, and the thermal-expansion, land-ice-melt and land-subsidence components of regional SLR to the end of the century. In addition, they considered both minimum and maximum global-mean SLR rates given by the A1B scenario (multiple-deterministic SRL approach). Alexandrakis et al. (2015) obtained shoreline retreats deterministically in the beach in front of Rethymnon city (Crete Island) for three time slices using the associated SLR global-mean values (deterministic SLR approach) by applying the Dean (1991) formula.

5.1.3. *Open beaches*

Open beaches are relatively long beaches (nearly) unprotected at their ends and where both cross-shore and longshore sediment transport are often essential components of the sediment budget. Current works at open beaches include the analysis of future wave-driven coastal sediment transport developed by Casas-Prat et al. (2016); Rosati et al.'s (2013) and Dean and Houston's (2016) modified Bruun Rule formulations used to assess SLR-induced shoreline response (the latter also recently applied by Karunarathna et al., 2018); the approach proposed by Vitousek et al. (2017) for predicting the shoreline evolution driven by longshore and cross-shore transport due to projected waves and SLR; the cross-shore model ensemble performed by Allenbach et al. (2015); and the assessment of SLR-driven shoreline retreats along the European sandy coasts presented by Thiéblemont et al. (2019). In addition, we include the studies presented by Le Cozannet et al. (2016, 2019), which focused on quantifying uncertainty in future shoreline change.

Casas-Prat et al. (2016) follow a top-down approach to evaluate future longshore and cross-shore sediment-transport volumes along the Catalan coast (Spain). These result from climate change projections in which an ensemble of five GCM-RCM configurations is performed under the A1B scenario (IPCC, 2007). The authors give particular emphasis to how inter-model variability translates from wave projections to wave-driven coastal impacts, in this case, through waves. Both the CERC equation (US Army Corps of Engineers, 1984) and Mendoza and Jimenez's (2006) erosion potential method are used to compute longshore and cross-shore sediment-transport rates, respectively. Using computationally non-expensive modelling tools allows assessing the suitability of each GCM-RCM combination considered to forecast changes in coastal dynamics. It is important to qualify that this work does not yield future shoreline change specifically. Instead, it provides projected wave-driven changes in sand volumes eroded after storm episodes, and the cumulative volumes lost over 30 years (without considering beach recovery), for the period 2071-2100 with respect to 1971-2000. However, we consider this contribution to be relevant for the review because of the use of regional wave projections to compute longshore and cross-shore erosion. The authors deal with the uncertainty added by the RCMs to the sediment transport response by analysing discrepancies in patterns of change of forcing wave parameters.

Rosati et al. (2013) developed a modified form of the Bruun Rule that deems the full range of parsing cross-shore transport from seaward to landward boundaries, based on the prevailing storm and surge conditions (overwash and aeolian processes) and whether there is a deficit or surplus of sand in the profile with respect to the equilibrium beach profile. The authors illustrated the framework deterministically in Cayo Costa (Florida) considering a rise in mean sea level of 0.5 m as the only climate-related driver.

Similar to Stive et al. (1991), Cowell et al. (2003), and Stive (2004), Dean and Houston (2016) proposed a sediment budget with the terms representing diverse phenomena affecting shoreline change. These phenomena include the Bruun-Rule recession, onshore transport, sediment sources (e.g., beach nourishment), sinks that take sand from the littoral system (e.g., ebb shoal growth, dredged material disposal outside the littoral zone), and longshore transport gradients. The application use the RCP SLR scenarios enhanced with land subsidence rates as climate-related drivers, yielding projected shoreline-change rates from 2015 to 2100, and assuming beach nourishment at the rate from 1972 to 2007. The authors sample uncertainty by using an ensemble of SLR scenarios and considering the mean values and standard deviations in both relative SLR scenarios and sediment transport rates.

Le Cozannet et al. (2016) presented a subjective-probability approach focused on quantifying uncertainty in the evolution of sandy shorelines under the Bruun Rule assumption. They adopt the sedimentary budget proposed by Stive (2004) and a beta SLR distribution with a regional deviation (probabilistic global SLR projections) to provide future shoreline changes that account for uncertain hydro-sedimentary processes in low- and high-energy coasts. This application is generic and considers the case of idealized wave-exposed sandy beaches with infinite sand availability, for which the authors define realistic probability functions for the parameters involved in the sand budget: Bruun-Rule recession, storm wave-induced retreat, aeolian transport, cross-shore effects (e.g., wave-nonlinearity-driven onshore sand transport), and longshore sedimentary processes with and without groins. Le Cozannet et al. (2016) use ranges of typical values provided by Stive (2004) that were based on observations in the Netherlands and Australia. Using a quasi-Monte-Carlo approach, uncertainties propagate through the model and shoreline projections are provided in probabilistic terms. Ultimately, the authors perform a global sensitivity analysis (Saltelli et al., 2008) to determine the contribution of each uncertain input parameter to the variance of the model outcome.

Following a top-down approach, Vitousek et al. (2017) proposed a modular scheme integrating longshore and cross-shore transport induced by GCM-projected waves and regional SLR estimates, which applies to both open and small pocket sandy beaches (in the latter case, disabling the longshore component). The model is composed by longshore transport due to waves following a one-line approach (Larson et al., 1997); cross-shore transport due to waves using an equilibrium shoreline change model (Yates et al., 2009; Long and Plant, 2012); and cross-shore transport due to SLR employing an equilibrium beach profile change model (Bruun, 1962). The application of the model to the forecast period (2010-2100) provides the shoreline evolution over the next 90 years due to projected time series of wave conditions derived from one GCM-RCM composition combined with seven regional SLR scenarios. Uncertainty is therefore sampled by considering an ensemble of SLR scenarios. A relevant aspect is that the model is somewhat empirical, as key model parameters are auto-selected using an extended Kalman filter for data assimilation to optimise the match between data and model hindcasts. The algorithm of data assimilation helps reduce epistemic uncertainty associated with the erosion model.

Similar to Monioudi et al. (2017), Allenbach et al. (2015) developed an analysis of SLR-induced erosion on the Black Sea open beaches. They provide statistics of shoreline retreat obtained by the application of an ensemble of six cross-shore erosion models (the longshore-transport component is neglected). These include Bruun (1988), Dean (1991); Edelman (1972); Leont'yev (1996), XBeach (Roelvink et al., 2010), and SBEACH (Larson and Kraus, 1989). Following more than 17000 experiments that combine different wave conditions (significant wave heights of 0.5-6 m and periods of 3-12 s), seven median (d_{50}) grain sizes, five linear profile slopes, and eleven SLR scenarios (ensemble SLR approach assuming increases up to 2 m), the means (best fits) of the lowest and highest projections by the model ensemble are estimated. In their study, results from all models have equal weighting in the ensemble projected ranges of shoreline recession; and uncertainty is considered in terms of statistic aggregates (e.g., mean value and variance).

Karunarathna et al. (2018) carried out an assessment of past and future changes on a dune-fronted beach along the Sefton coast (Liverpool Bay, UK). The authors model the dune response to extreme waves and water level events using XBeach (Roelvink et al., 2010), and the SLR-induced medium-long term (i.e., multidecadal) shoreline change through the application of Dean and Houston's (2016) modified Bruun Rule. XBeach, which does not currently reproduce beach recovery, and hence is restricted to short-term applications, is implemented to simulate historical 2D morphodynamic change during past storm conditions (including cross-shore and longshore transport). Climate change is only considered to obtain medium-long term erosion. The assessment provides rates of beach change for an ensemble of six regional SLR scenarios.

At the European scale, Thiéblemont et al. (2019) presented a first estimate of the contribution of regional SLR to coastal erosion on sandy coasts under likely and high-end sea-level rise scenarios by the end of the twenty-first century. The authors developed pan-European high-end scenarios based on the upper bound of the RCP8.5 scenario and on high-end estimates of global and regional components of sea-level projections considering their uncertainty (e.g., using a multi-model ensemble and the AR5/SROCC median and likely ranges). Shoreline changes along the European coast are estimated using the Bruun rule (Bruun, 1962) for an ensemble of three regional SLR scenarios.

More recently, Le Cozannet et al. (2019) presented an objective-probability approach aimed at quantifying uncertainty in shoreline change projections due to SLR. The authors estimate the uncertainty related to the coastal erosion model by comparing two approaches in the coast of Aquitaine (France): the Bruun Rule and the PCR model (described in **section 4.1.1**). The results indicate that the equilibrium response of the PCR in the study region can be emulated by the Bruun Rule equation with modified foreshore slopes (i.e., the PCR surrogate model). Assuming no human interventions, inlets nor other major sediment sources/sinks, a sediment budget that considers the PCR surrogate model and the effects of longshore gradients in sediment transport derived empirically is set up. The approach provides projected shoreline changes in probabilistic terms, in which uncertainty is sampled using probabilistic regional SLR projections associated with three RCPs (Kopp et al., 2014) and defining probability functions that account for uncertainty in vertical ground motions, observed longshore sediment trends, and shoreface beach slopes. The PCR surrogate model has negligible computation costs and allow to perform a global sensitivity analysis (Saltelli et al., 2008), which requires thousands of simulations to quantify the uncertainty associated with different aspects.

5.2. Inlet-interrupted coasts

Shorelines near inlets are influenced not only by climate change-related drivers affecting uninterrupted coasts but also by impacts that inlets can have on their evolution. Ranasinghe et al. (2013) and Toimil et al. (2017) studied the climate change-induced effects that wave- and tide-dominated estuaries can lead to in adjacent coasts, respectively. The first yields the maximum potential beach retreat that may occur by 2100; the second incorporates these effects into a shoreline evolution model, providing hourly shoreline changes over the whole century. Both studies succeed in proving that not considering sediment demands/supplies others than the Bruun effect (Bruun, 1962) in the sand budget of these systems may well lead to misleading shoreline change estimates, which had already been recognised before (e.g., Stive, 2004). Ranasinghe et al. (2013) addressed this issue by developing a scale-aggregated model for wave-dominated, micro-tidal environments, which have little or no intertidal flats, backwater marshes or ebb tidal deltas. In this work, the physical processes considered to contribute to shoreline change are the SLR-driven Bruun effect (Bruun, 1962), the basin infilling due to the SLR-induced increase in basin accommodation space, and the basin volume change due to climate change-driven increases or decreases in river flow and increases or decreases in fluvial sediment supply. The model is applied deterministically to assess long-term shoreline retreat at four inlets including the Wilson Inlet and the Swan River System (Australia), without providing uncertainty estimates. The authors use global SLR projections (deterministic SLR approach), rainfall and river inflow (IPCC, 2007). More recently, a slightly-modified version of this model was applied by Bamunawala et al. (2019) to the same inlet systems. The only difference between this approach and Ranasinghe et al.'s (2013) is the method adopted to quantify the fluvial sediment supply. Bamunawala et al. (2019) includes the effects of additional factors such as changes in temperature, land use and land management practices.

Toimil et al. (2017) proposed a simplified scale-aggregated model for tide-dominated, macro-tidal environments in response to climate change-modified forcing. The model was applied to five inlet systems in Asturias, a coastal region in the North of Spain. According to the nature of these inlets, the physical processes considered as shoreline-change contributors are the SLR-driven landward displacement of the coastline (Bruun, 1962), the basin infilling due to the SLR-induced increase in basin accommodation space, and the SLR-driven ebb tidal delta volume change. In this case, fluvial sediment supply is considered negligible as the estuaries included in the assessment are regulated by dams or permanently dredged. The authors couple the SLR-induced shoreline recession due to basin infilling and ebb tidal delta volume change (acting as longshore sinks) with the shoreline evolution model described in **Section 4.1.1** to obtain probabilistic estimates of hourly shoreline changes from 2010 to 2100. Within this probabilistic approach, uncertainty is sampled by combining thousands of synthetic multi-variate time-series of waves and storm surges with three SLR possible evolutions related to the RCP8.5 mean and standard deviation values (multiple-deterministic SLR approach). Importantly, it should be noted that the use of the equilibrium formulation to describe the complex behavior of an inlet is based on simplifying assumptions. For example, considering that the estuary and its elements reach a dynamic equilibrium state, since the formulation are not able to describe either their temporal evolution or their spatial distribution. Additionally, there is a lag between SLR and the system's morphological response. Ranasinghe et al. (2013) considered a linearized single-element version of ASMITA (Aggregated Scale Morphological Interaction between a Tidal-inlet system and the Adjacent coast) only valid for small inlet-basin systems (van Goor et al., 2003), in which they showed that this lag effect could be represented by including a coefficient in the basin-infilling equation.

ASMITA is a scale-aggregated model first developed by Stive et al. (1998) and based on the conservation of sediment within a three-element system (ebb delta, channel, and basin) and the adjacent nearshore area (beach). The model assumes that the morphological interaction between the three system elements are due to diffusive sediment transport and that the system is in morphological equilibrium if undisturbed. When the system is perturbed (e.g. due to SLR), the three elements change their volume and evolve towards an empirically specified dynamic equilibrium state. Under this condition, the basin borrows sand from the adjacent beach to satisfy a demand that is proportional to the rate of SLR. Hinkel et al. (2013) undertook the first global analysis of erosion of sandy beaches due to global-mean SLR including an adapted version of ASMITA (Stive and Wang, 2003). The authors developed and applied a simple first-order erosion model in which SLR-induced shoreline recession is obtained considering the direct effect of profile translation on open sandy beaches (i.e., the Bruun effect) and the indirect erosion near selected tidal inlets and estuaries. Climate uncertainty is sampled by considering an ensemble of SLR scenarios and three climate sensitivities.

5.3. Summary of reviewed works

In order to summarize the major differences and similarities between the works described above, **Tables 3** and **4** provide a classification based on the following criteria: coastal typology, coastal processes, climate-related drivers, approaches to deal with uncertainty and type of outcomes (boxes 1, 3, 4 and 5 in **Fig. 2**). **Table 3** illustrates for typology the relation between the coastal processes modeled and the climate-related drivers considered. The columns corresponding to sinks and sources refer to any transport other than strictly cross-shore or longshore. The row corresponding to *others* includes non-climate drivers and non-modeled sediment-transport rates. **Table 4** reflects for each typology the relation between the approaches used to consider uncertainty (described in **Table 1**) and the type of outcomes provided.

Finally, **Fig. 3** shows some of examples of the coastal sites investigated in the reviewed papers, which include uninterrupted (small pocket, long embayed and open beaches) and inlet-interrupted coastlines in temperate environments, displayed in alphabetical order.

	Cross-shore transport	**Longshore transport**	**Sediment sinks**	**Sediment sources**
	Uninterrupted coasts			
	Small pocket beaches			
Waves	Toimil et al., 2017; Monioudi et al., 2017			
Storm surges	Toimil et al., 2017; Monioudi et al., 2017			
Tides	Toimil et al., 2017			
Sea-level rise	Toimil et al., 2017; Monioudi et al., 2017			
	Long embayed beaches			
Storms**	Ranasinghe et al., 2012; Wainwright et al., 2015; Jongejan et al., 2016			
Waves	Yoshida et al., 2013; Alexandrakis et al., 2015	Zacharioudaki and Reeve, 2011		
Sea-level rise	Snoussi et al., 2009; Ranasinghe et al., 2012; Yoshida et al., 2013; Alexandrakis et al., 2015; Wainwright et al., 2015; Jongejan et al., 2016;			
	Open beaches			
Waves	Casas-Prat et al., 2016*; Vitousek et al., 2017; Allenbach et al., 2015	Casas-Prat et al., 2016*; Vitousek et al., 2017		
Sea-level rise	Rosati et al., 2013; Dean and Houston, 2016; Le Cozannet et al., 2016; Vitousek et al., 2017; Le Cozannet et al., 2019; Allenbach et al., 2015; Karunarathna et al., 2018; Thiéblemont et al., 2019			
Others	Le Cozannet et al., 2019	Dean and Houston, 2016; Karunarathna et al., 2018; Le Cozannet et al., 2016, 2019	Rosati et al., 2013; Dean and Houston, 2016; Le Cozannet et al., 2016; Vitousek et al., 2017; Karunarathna et al., 2018	Rosati et al., 2013; Dean and Houston, 2016; Le Cozannet et al., 2016; Vitousek et al., 2017; Karunarathna et al., 2018
	Inlet-interrupted coasts			
Waves	Toimil et al., 2017			
Storm surges	Toimil et al., 2017			
Tides	Toimil et al., 2017			
Sea-level rise	Hinkel et al., 2013; Ranasinghe et al., 2013; Toimil et al., 2017		Ranasinghe et al., 2013; Toimil et al., 2017; Bamunawala et al., 2019	
River discharge			Ranasinghe et al., 2013; Bamunawala et al., 2019	Ranasinghe et al., 2013; Bamunawala et al., 2019
Others				Hinkel et al., 2013

Table 3 Classification of the post AR4 reviewed papers emphasizing the relation between the coastal processes modeled and the climate-related drivers considered. Note that for organization purposes we assigned the studies that

cover more than one coastal typology (i.e., regional assessments) to the category (or categories) they are most relevant for. (*): provides projected wave-driven changes in erosion volumes rather than shoreline change specifically. (**): erosion model forcing derived from the combination of wave parameters, tidal anomaly and storm duration.

	Deterministic	**Multiple-deterministic**	**Ensemble**	**Objective/ Subjective-probability**	**Probabilistic**
	Uninterrupted coasts				
	Small pocket beaches				
Extreme retreats			Monioudi et al., 2017		Toimil et al., 2017
Mid-term change					Toimil et al., 2017
Long-term change			Monioudi et al., 2017		Toimil et al., 2017
	Long embayed beaches				
Extreme retreats					Ranasinghe et al., 2012; Wainwright et al., 2015; Jongejan et al., 2016
Short-/mid-term variability			Zacharioudaki and Reeve, 2011		
Long-term change	Alexandrakis et al., 2015	Yoshida et al., 2013	Snoussi et al., 2009; Zacharioudaki and Reeve, 2011		Ranasinghe et al., 2012; Wainwright et al., 2015; Jongejan et al., 2016
	Open beaches				
Extreme retreats			Allenbach et al., 2015; Casas-Prat et al., 2016*; Vitousek et al., 2017		
Short-/mid-term variability			Casas-Prat et al., 2016*; Vitousek et al., 2017		
Long-term change	Rosati et al., 2013;		Allenbach et al., 2015; Dean and Houston, 2016; Casas-Prat et al., 2016*; Vitousek et al., 2017; Karunarathna et al., 2018; Thiéblemont et al., 2019	Le Cozannet et al., 2016, 2019	
	Inlet-interrupted coasts				
Extreme retreats					Toimil et al., 2017
Short-/mid-term variability					Toimil et al., 2017
Long-term change	Ranasinghe et al., 2013; Bamunawala et al., 2019		Hinkel et al., 2013		Toimil et al., 2017

Table 4 Classification of post AR4 reviewed papers emphasizing the relation between how uncertainty is considered, and the type of outcomes provided. Note that for organization purposes we assigned the studies that cover more than one coastal typology (i.e., regional assessments) to the category (or categories) they are most relevant for. (*): provides projected wave-driven changes in erosion volumes rather than shoreline change specifically.

6. Discussion

Developing future projections of shoreline changes that include the effects of climate change and provide robust uncertainty estimates is a major challenge that requires a comprehensive framework. Currently, there is no fully satisfactory coastal erosion model that allows coupling of hydrodynamics and morphodynamics; reproduces short-, mid- and long-term shoreline changes accurately, and is not highly computationally time-consuming, enabling the consideration of uncertainty through the complete top-down approach (according to **Fig. 1**). Furthermore, our incomplete understanding of the littoral sediment transport mechanisms (box 3 in **Fig. 2**), our inability to represent fully the hydrodynamics of the surf zone (box 1 in **Fig. 2**), our (limited but growing) computational resources, and the deep uncertainty in projected shoreline-change drivers (**Fig. 1**) are good reasons to think that such an "ideal" approach may well be some time in the making. In the interim, this review demonstrates the significant progress made since the AR4 release to develop a range of methods and physics-based models to assess coastal erosion under climate change. It also highlights that more remains to be done, including the identification of some key research gaps.

For any geomorphic environment (box 2 in **Fig. 2**) and GHG emissions scenario (box 1 in **Fig. 2**), coastal managers would benefit from knowledge on the time evolution of the mean or median shoreline position, the likelihood of extreme retreat events associated with different return periods (box 4 in **Fig. 2**), and the quantification of the associated uncertainty, which accumulates through the top-down approach (box 5 in **Fig. 2**), to make better decisions. For that purpose, considering an ensemble of climate change scenarios (e.g., the RCPs based on GHG and aerosol concentrations), future time series of coastal drivers such as mean sea level, waves, storm surges, tides, and fluvial discharge if applicable, need to be downscaled to the beach system (**Fig. 1**). However, there is no study yet available that fully incorporates and appropriately combines future time series of these dynamics to obtain estimates of climate change-driven shoreline change. Only three research works have implemented dynamical projections of waves (i.e., Zacharioudaki and Reeve, 2011; Casas-Prat et al., 2016; Vitousek et al., 2017) considering one or more GCM-RCM configurations. Nevertheless, none of them correct the bias before using RCM (or GCM, if this were the case) output as boundary conditions for regional coastal forcing and erosion models (**Fig. 1**), which probably results in misleading probability distribution functions of shoreline recession, particularly in the tails, reducing the ability to reproduce extreme events. Further, bias correction techniques can improve statistics that depend strongly on the temporal sequence of the original field (Dosio and Paruolo, 2011; Charles et al., 2012). This is especially important for coastal erosion given the demonstrated influence of the chronology in extreme retreat events (e.g., Toimil et al., 2017). Another striking aspect is the lack of consideration of uncertainty in the internal variability of climate models (**Fig. 1**), for instance, through different model initialisations and realisations. While it is true that inter-model variability can overshadow the internal variability of the models themselves and it may not affect the average climatology significantly, it may influence the day-to-day model solution, modulating or masking physically forced signals, and even leading to the amplification of climate variability, and consequently affecting shoreline change estimates.

The simulation of the coastal erosion model is placed at the base of the uncertainty cascade (**Fig. 1**). When it comes down to this step, the model ideally has to be run with at least hundreds of combinations of the forcing variables that would already account for the uncertainty associated with the emissions scenarios and GCM-RCM configurations to sufficiently quantify uncertainty (Ranasinghe, 2016). However, within the scope of this review, there are only two different methodologies developed and applied so far that allow modelling of coastal erosion probabilistically (i.e., Ranasinghe et al., 2012;

Toimil et al., 2017), both relying on robust statistical models to stochastically generate synthetic time series of coastal erosion drivers. These studies have made a significant step forward to accommodate the new demand for risk-based informed coastal planning frameworks, although none of them sample uncertainty through all the steps within the top-down process (**Fig. 1**). Furthermore, only one study uses probabilistic SLR projections and combines them with other coastal drivers (i.e., Le Cozannet et al., 2019). Finally, few studies attempt to quantify (or partially reduce) uncertainty associated with the erosion models themselves, arising from their sensitivity to multiple factors, their dependence on many empirical parameters, and their failure to realistically simulate coastal processes (the so-called epistemic uncertainty, see **Fig. 1**). There are four works addressing uncertainty in this regard: Allenbach et al. (2015) and Monioudi et al. (2017) consider model uncertainty by performing coastal erosion model ensembles; Le Cozannet et al. (2019) carry out a variance-based global sensitivity analysis to quantify the uncertainty associated with the erosion model; and Vitousek et al. (2017) reduce model uncertainty by applying an algorithm of data assimilation. While approaches with a certain level of probabilistic development enable uncertainty to be quantified, accuracy in coastal erosion modelling can only be increased by using better datasets (e.g., climate change drivers such as projected sea level or waves with higher spatial and temporal resolution), improving our knowledge on coastal processes and sediment transport mechanisms (e.g., progressing in detection and attribution), and developing better erosion models (e.g., calibrated and validated with field data and with enhanced model parameterizations).

7. Conclusions and suggestions for good practice

The assessment of shoreline change is a complex site-specific issue. The most influential factors include the physical characteristics of sediment, local wave and sea level conditions, the bathymetry, as well as the orientation, configuration and exposure of the coast. Over the last decade there has been important progress towards improving our knowledge and information base (climate-change coastal drivers) and developing and implementing more comprehensive methodologies to assess coastal erosion due to climate change, the key components of which could be organised as presented in **Fig. 2**. However, further research is still needed to integrate drivers and processes appropriately, and to provide more robust projections of shoreline change according to decision makers' needs, including uncertainty estimates. Considering our present understanding and resources, and the application at the scale of coastal management, the following five suggestions could be considered good practice in the field.

First, consideration of the full range of climate-related forcing conditions (box 1 in **Fig. 2**) driving shoreline change alongside any other sediment sink and source relevant to the sediment budget (box 3 in **Fig. 2**). For example, neglecting the effect of waves and storm surges and assuming sea-level rise as the only driver for coastal erosion may misrepresent the impact of climate change and result in insufficient action or even maladaptation (e.g., Summers et al., 2018). This could be crucial for coastal managers who require knowledge of the likelihood of occurrence of extreme retreat events associated with specific return periods in the future. Further, although sediment sinks and sources are mostly linked to sediment transport mechanisms (e.g., sand dredging and nourishment, sediment trapping, headland erosion, aeolian transport), they can also include other processes such the effects of a compressible substrate, which can be important for beaches that overlay mud or peat deposits (e.g., Rosati et al., 2010).

Second, ensuring consistency between coastal erosion drivers and processes, attempting to reproduce them accurately (boxes 1 and 3 in **Fig. 2**). Detailed process-based models capable of resolving the hydrodynamic and morphologic forcing are often prohibitive in computation terms to simulate long-term shoreline change, although they do not necessarily provide improved skills over simplified models (French et al., 2015). However, the development of process-based models that can simulate 100 years of 2DH morphological evolution within a few minutes could become a realistic alternative to simpler and more efficient physics-based models (e.g., equilibrium beach profile and shoreline evolution models, and one-line models), which are to date the most used to compute climate change-driven erosion. In either case, there are critical aspects that need to be considered when modelling coastal erosion. For instance, using sequences of design storms instead of time-series of waves, storm surges and tides to derive storm erosion requires incorporating storm spacing as an additional forcing parameter within the statistical model (e.g., Callaghan et al., 2008). A similar rationale applies for beach recovery, a weak link in morphodynamic understanding that needs to be accounted for appropriately when modelling erosion beyond the scale of a single storm (Karunarathna et al., 2018), even if this requires empirical treatment (Ranasinghe et al., 2012). Other examples include estimating inlet-induced effects approximately when not implementing a process-based 2DH/3D model (Ranasinghe et al., 2013; Toimil et al., 2017; Bamunawala et al., 2018); and not to consider beaches as infinite but recognise that they have boundaries constrained by geomorphic or human settings. These boundaries can be considered part of the coastal system and modelled in an integrated fashion in sandy beaches, following an approach similar to Walkden and Hall (2005) for soft-rock shores.

Third, the progression from single event (e.g., storms) to multidecadal/centennial timescales may require increased generalization of modelling approaches (Cowell et al., 2003). However, solid understanding of processes is fundamental to support any simplifying assumption (box 3 in **Fig. 2**). For example, assuming a stable bathymetry is only acceptable if two conditions are met. The first condition is that rapid-onset dynamics (i.e., waves and storm surges) are constant. A second requirement is that no human action is to be made. It is important that this model generalization does not necessarily imply low-resolution outcomes, which ultimately shall meet coastal managers' requirements.

Fourth, uncertainty ideally needs to be considered across all components of the model framework (box 5 in **Fig. 2**). This involves uncertainty sampling not to be limited to executing the impact model several times with different climate-related drivers, for example, with many GCM-RCM configurations, multiple chronologies of waves and storm surges (or storm events), and probabilistic sea-level rise. There are other uncertain factors that may influence shoreline change such as sediment transport-related processes, model parameters, and the initial coastal configuration, which could also be couched probabilistically. Considering the whole range of uncertainty through the complete process of modelling climate change-driven coastal erosion would lead to a fully probabilistic approach (**Table 5**). Although it is not realistic to expect to achieve fully probabilistic assessments in the near future, other uncertainty perspectives such as extra-probabilistic theories derived from the study of sea-level rise may be worth exploring in the field of erosion modelling (also included in **Table 5**). This could be achieved by integrating complementary information such as expert judgement into the probabilistic confidence intervals (e.g., using the maximum entropy principle as in Le Cozannet et al., 2016). Further, more emphasis could be given to low-probability high-consequence impacts. The effects of combining likely and high-end scenarios have been considered for sea-level rise, but much less so for other important forcing variables such as waves and storminess.

Potential uncertainty approaches	Descriptions adopted in this paper	Experience
Extra-probabilistic	Credible probability functions conveying aleatoric uncertainties as well as uncertainties on the shape of the distribution itself.	Inherited from sea-level rise
Fully probabilistic	The full space of input data and model parameters are characterised through probability distributions.	Not realised yet

Table 5 Potential approaches to address uncertainty in climate change-driven coastal erosion modelling (also displayed in box 5 in **Fig. 2**).

Finally, stakeholders' needs play a fundamental role in defining the required model outcomes (box 4 in **Fig. 2**) and indirectly the selection of the models to be used. If the objective is to obtain an estimate of the magnitude of an extreme recession at a time horizon, a shoreline evolution model would ideally need to be configured and applied time series (or appropriately reduced time-series) of relevant system forcing that extend at least to the target time horizon. Working with high-resolution time-series of shoreline evolution may also allow the analysis of shoreline changes at seasonal, interannual and interdecadal time scales. Instead, if one wants to know the long-term net recession, working with time-series of shoreline change may not be indispensable. In either case, coastal managers would benefit from the full range of probable magnitudes and their associated uncertainty to make sound decisions about risk reduction and adaptation in the context of current practice and governance arrangements. An alternative may consist of shifting from predicting top-down approaches that use scenarios to provide future shoreline changes to resilience-oriented bottom-up approaches, in which the focus is on first identifying stakeholder's needs and preferences (e.g., risk aversion), and then co-producing the most appropriate method accordingly. Participatory appraisals may offer great promise in this regard.

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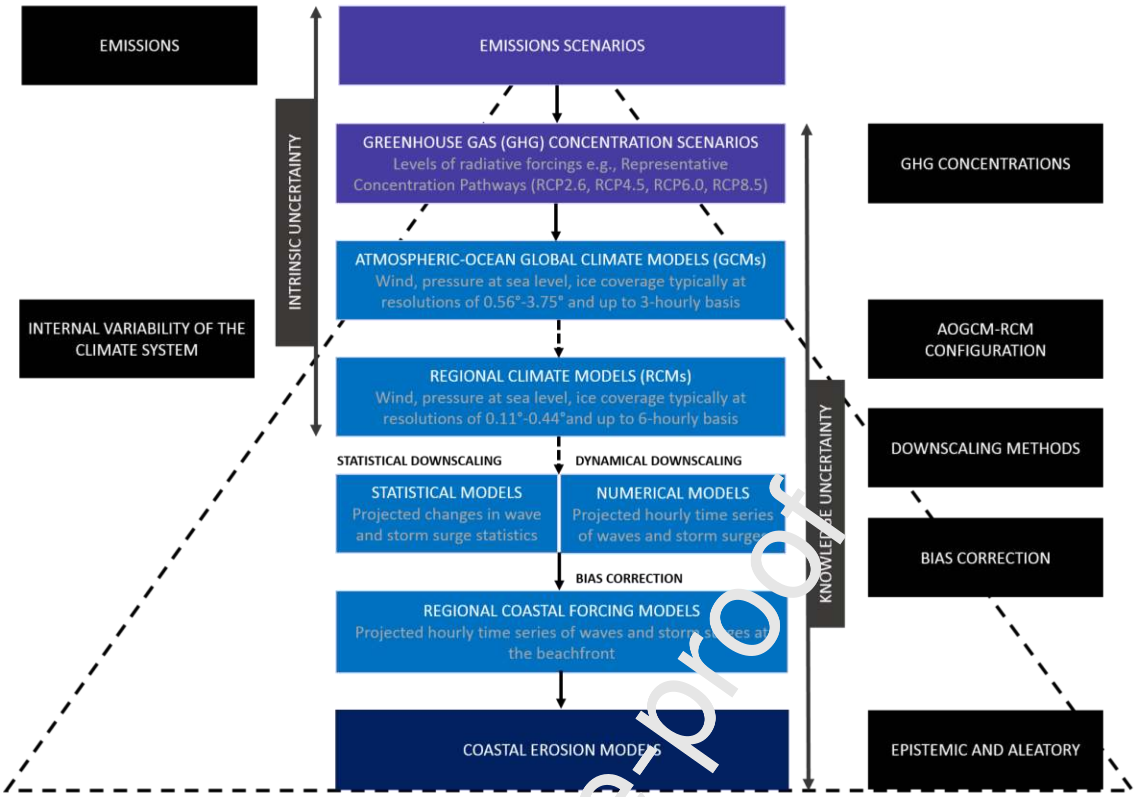

Figure 1 Generic sequence of comprehensive steps followed in top-down assessments of climate change-driven coastal erosion and associated sources of uncertainty that cascade through the whole process (based on Ranasinghe, 2016). As an example, it illustrates how projected waves and storm surges can be derived. Note: the figure shows a general outline and the uncertainty cascade expanding from top to bottom does not necessarily follow a linear sequence.

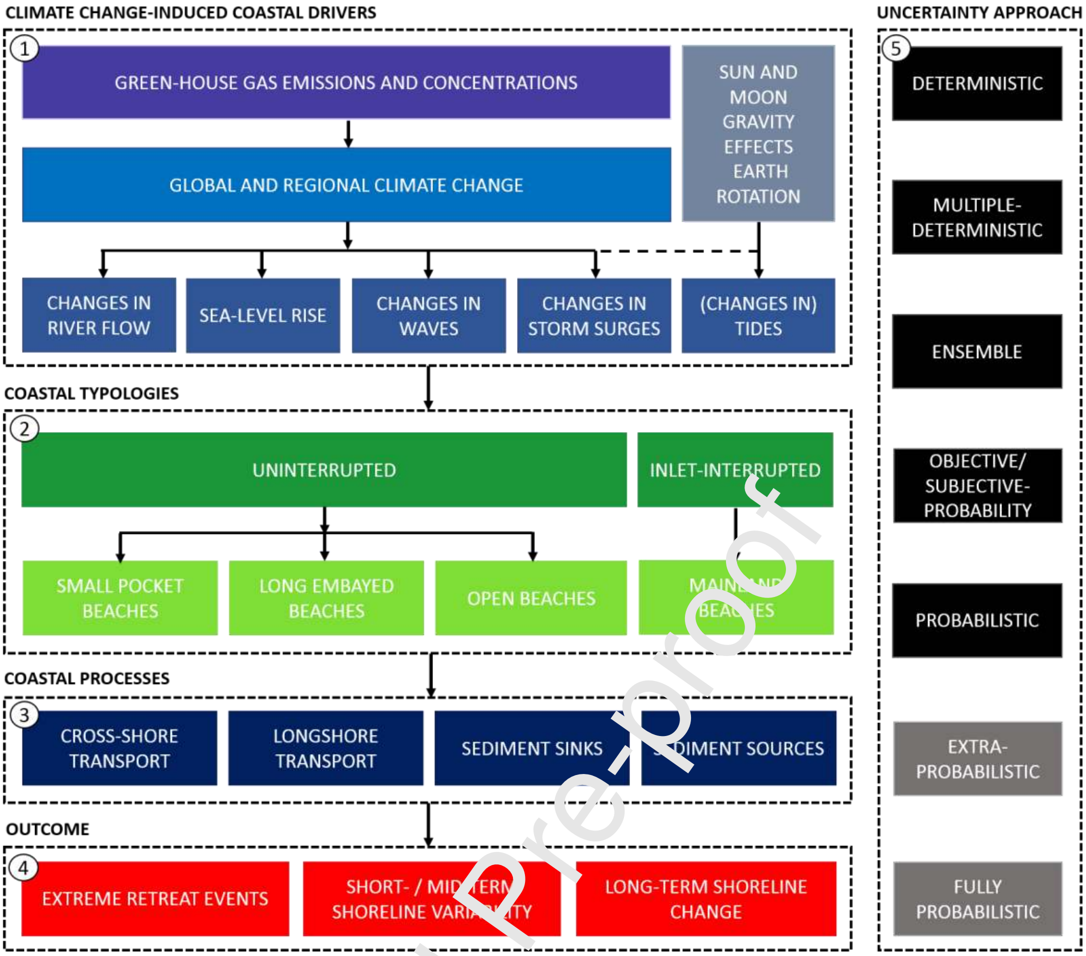

Figure 2 Main components involved in the modelling of climate change-driven coastal erosion on sandy beaches.

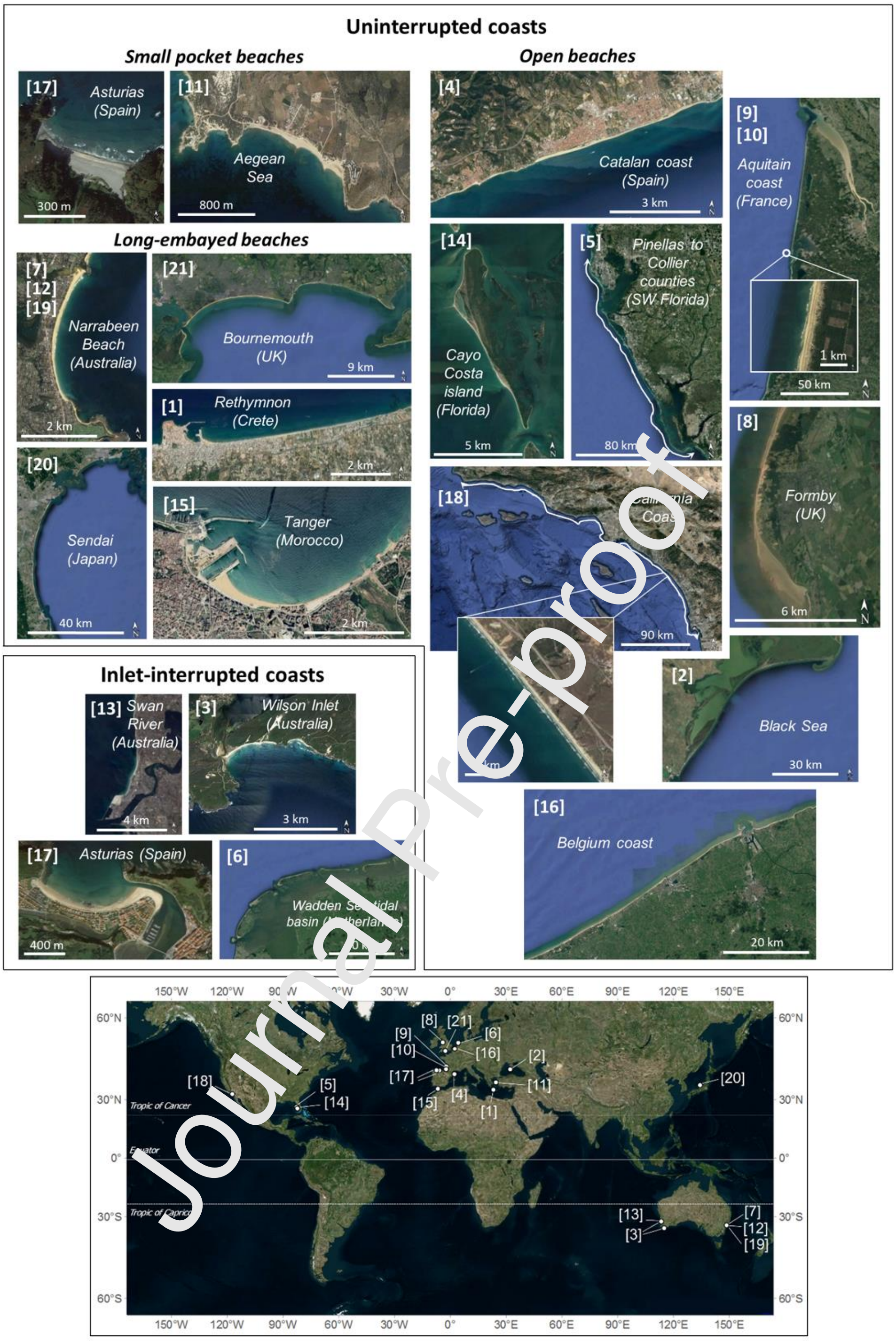

Figure 3 Illustration of some of the coastal sites investigated in the reviewed papers, which include uninterrupted (small pocket, long embayed and open beaches) and inlet-interrupted coasts. Following the alphabetical order, numbers refer to [1] Alexandrakis et al. (2015), [2] Allenbach et al. (2015), [3] Bamunawala et al. (2019), [4] Casas-Prat et al. (2016), [5] Dean and Houston (2016), [6] Hinkel et al. (2013), [7] Jongejan et al. (2016), [8] Karunarathna et al. (2018), [9] Le Cozannet et al. (2016), [10] Le Cozannet et al. (2019), [11] Monioudi et al. (2017), [12] Ranasinghe et al. (2012), [13] Ranasinghe et al. (2013), [14] Rosati et al. (2013), [15] Snoussi et al. (2009), [16] Thiéblemont et al. (2019), [17] Toimil et al. (2017), [18] Vitousek et al. (2017), [19] Wainwright et al. (2015), [20] Yoshida et al. (2015), [21] Zacharioudaki and Reeve (2011). Basemaps are from Google Earth.

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